

Wavelet-based filter for PD signal processing

Abstract. This communication letter deals with the wavelet transformation as it was used for to partial discharge (PD) signal processing. The background of the phase resolved partial discharge analysis is referenced. The algorithm of wavelet multi-scale decomposition for PD signal processing is shown. Experimental PD data has been processed. The multi-scale analysis and reduction of signal-overlapping noise are presented.

Keywords: partial discharges, wavelet, signal processing, threshold

Introduction

It is known that the activity of partial discharges become evident as discharge magnitude and discharge timing. The discharge magnitude is represented by apparent charge (as specified in [1]) and discharge timing means the position of the discharge pulse related to the voltage cycle of the test voltage. The digital PD data might contain all necessary information about PD activity recorded in certain time. PD data are stored in digital storage media. We can see also attempts of several scientists to suggest PD format standard e.g. [2]. The minimal structure of PD data could obtain two fields: the discharge magnitude and corresponding time. PD data stored in data media are further processed by computer aided analysis. A lot of efforts have been dedicated to the development of the mathematical analysis of PD activity. By using a statistical mathematical methods well-known partial discharge phase resolved analysis were specified. The principle has been written many times by various authors, e.g. [3]. Partial discharges are phenomenon with spatio-temporal development. Another works have dealt with analysis of stochastic character of discharge activity. The methods of time-series analysis which respect stochastic behavior of PD phenomena were applied to reach new descriptors of PD process [4,5]. Relatively new possibilities in the field of PD analysis have been added by applying of the wavelet transformation. The wavelet transformation gives new analytical views to PD activity research. Moreover it may be driven by various ways, for example there are known using the wavelet transformation for classification of multi-source PD patterns [6]. The research of acoustic emission of PD became standalone branch of large PD research area. The state of the art advances lie on using statistical tool [7] and also wavelet classification of PD modulated ultrasonic emission [8]. The distinction of PD origins belongs to the basic problems when composite insulation is tested or in the case of high structured device PD tests.

Methods

PD distributions have been calculated: H_{qn} , H_{qmean} and H_{qmax} which are also called the derived characteristics. They are calculated by means of mathematical statistics [9-11].

The Wavelets

The wavelet means small wave. The wavelet analysis exploits an idea that the signal is expanded on a set of dilated or compressed functions

$$(4) \quad \Psi_{a,b}(t) = |a|^{-0.5} \Psi\left(\frac{t-b}{a}\right)$$

The dilation a is the factor that allows to change both time and frequency resolution when analysing the signal. For better imagination the reader could imagine that the

parameter a is similar as the scale used in maps or technical drawings.

The b is translating coefficient. It is provided that $a, b \in \mathcal{R}$ and $a \neq 0$. The transforming function $\psi(t)$ is also called as the mother wavelet. A continuous-time wavelet transform of the function $f(t)$ is defined as [9]

$$(5) \quad CWT_{\psi} f(a, b) = W_f(b, a) = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t) \psi^*\left(\frac{t-b}{a}\right) dt$$

The multiplication of $|a|^{-0.5}$ provides energy normalization that's why the transformed signal will have the same energy at every scale. The original signal can be transformed with $W_f(b, a)$ sampling in dyadic grid

$$(6) \quad a = 2^{-m} \quad \text{and} \quad b = n2^{-m}$$

where $m, n \in \mathcal{Z}$. The substitution formulas (6) into (5) results as formula of a discrete wavelet transformation

$$(7) \quad DWT_{\psi} f(m, n) = \int_{-\infty}^{\infty} f(t) \psi_{m,n}^*(t) dt$$

where $\psi_{m,n}(t) = 2^{-m} \psi_{m,n}(2^{-m}t - n)$ is scaled and dilated mother wavelet $\psi(t)$. There are known many mother wavelet functions, e.g. Haar, Daubechies, Coiflets and many more. They differ in the manner how the signal is scaled and wavelet is defined. An example of visual interpretation of coefficients calculated for continuous wavelet transformation where input signal is sinus function is on Figure 2. Mother wavelet function is mexican hat.

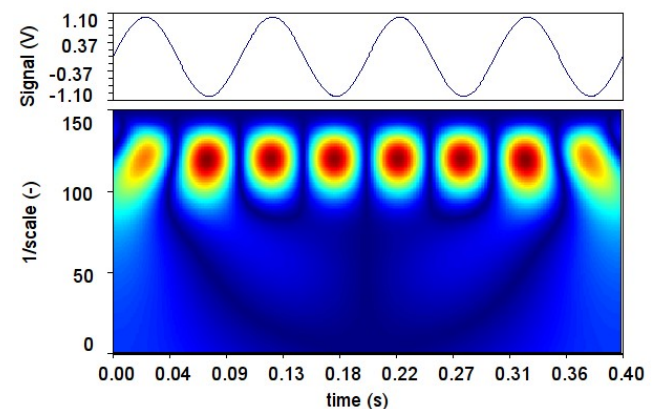


Fig.1. An example of four mother wavelets

The wavelet transformation has versatile exploitation. It can be used for multi-resolution signal analysis, wavelet-based de-noising of the signals moreover there are lot of further applications.

The de-noising procedure with wavelets have been described e.g. in [10]. It includes application of wavelet transformation to noisy PD signal, selection of proper threshold at each scale level determine hard or soft signal thresholding and finally providing inverse wavelet transformation of thresholded wavelet coefficients. Mother wavelet will not only determine how well we estimate the original signal in terms of the shape of the PD spikes, but also it will affect the frequency spectrum of the denoised signal. There are several methods to determine mother wavelet. The general approach is use criteria of the correlation γ between the PD signal and the wavelet-denoised signal

$$(8) \quad \gamma = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{(X - \bar{X})^2 (Y - \bar{Y})^2}$$

where \bar{X} is mean value of input signal set X and \bar{Y} is mean value of reconstructed signal set Y . For threshold limit setting we determine the noise variance guess given by

$$(9) \quad \hat{\sigma} = \frac{\text{Median}|C_{i,j}|}{0.6745}$$

where $|C_{i,j}|$ corresponds to the wavelet coefficients of the highest scale part of decomposition, where the most of the noise is present. Threshold value is finally given by fixed form threshold equation

$$(10) \quad T(\hat{\sigma}_X) = \hat{\sigma}^2 \cdot 2 \log \sqrt{N}$$

where N is number of wavelet coefficients $|C_{i,j}|$.

Results and discussion

PD measurements on both model and real insulating systems were done. Analog PD signal was digitized and analyzed. Wavelets de-noising of the signal were performed and PD patterns were created from the PD data. PD source was energized from non-ionizing hv transformer. PD signal was latched in the measuring impedance, digitized and stored for further processing. The attention was focused on discharges that originate from different PD sources: corona discharges with low amplitude of apparent charge and noise-overlapped surface discharges and internal discharges. The PD record of first five periods of the test voltage cycle is shown Figure 2, upper position. The original noise-overlapped signal with some significant corona PD pulses can be seen there. The discrete wavelet transformation by using Daubechies-8 wavelet, and performed a 6-level wavelet decomposition is applied for signal processing. With hard-threshold procedure, the six-levels decomposition has been applied to filter the noise. In presented case the threshold was set to the value 2.5-times of the standard deviation of the wavelet-decomposed signal at each level. The denoised signal at each scale level is shown in Figure 2, at its lower position.

Conclusion

The improving of the PD analysis is possible by application of wavelet-based noise filter. The method can be used for very sensitive measurements or for the case of

strong disturbances. It is applicable for on-line diagnostics of hv power equipments and apparatus.

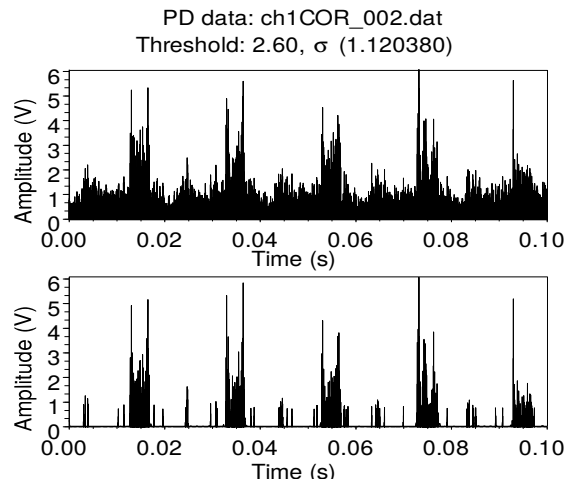


Fig.2. Original (upper) and denoised (lower) corona PD impulses

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Author: Juraj Kurimský, Katedra elektroenergetiky, Fakulta elektrotechniky a informatiky Technickej univerzity v Košiciach, Letná 9, 042 00 Košice, E-mail: juraj.kurimsky@tuke.sk